

## MEASURING AI FLUENCY AMONG BUSINESS STUDENTS: A TECHNOLOGY ACCEPTANCE MODEL APPROACH FOR DIGITAL TRANSFORMATION IN INDONESIAN HIGHER EDUCATION

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### Abstract

This study examines AI fluency among business students in Indonesian higher education by extending the Technology Acceptance Model (TAM) with AI literacy, digital self-efficacy, and institutional support. Using a quantitative survey of 385 business students at Universitas Bunda Mulia, data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that AI literacy significantly predicts perceived usefulness ( $\beta = 0.521$ ,  $p < 0.001$ ), perceived ease of use ( $\beta = 0.486$ ,  $p < 0.001$ ), and behavioral intention to use AI tools ( $\beta = 0.412$ ,  $p < 0.001$ ). Attitude also predicts behavioral intention ( $\beta = 0.328$ ,  $p < 0.001$ ), while digital self-efficacy strengthens the relationship between AI literacy and behavioral intention ( $\beta = 0.256$ ,  $p < 0.001$ ). Institutional support positively influences both perceived usefulness and perceived ease of use, although with smaller effect sizes. The model explains 52.3% of the variance in behavioral intention. The study contributes by clarifying the conceptual boundary between AI literacy and AI fluency within an extended TAM framework and by showing how individual confidence and institutional support condition AI adoption among Indonesian business students. Because the study uses cross-sectional self-reported data from a single institution, the findings should be interpreted as evidence of perceived and intention-based AI fluency rather than objective AI performance or causal development over time.

**Keywords:** AI fluency, AI literacy, technology acceptance model, digital self-efficacy, institutional support, business education, higher education, Indonesia

## INTRODUCTION

The integration of artificial intelligence (AI) into higher education represents one of the most significant transformations in contemporary learning environments (Chiu et al., 2024; Zawacki-Richter et al., 2019). As AI technologies become embedded in business operations, higher education institutions are increasingly expected to prepare graduates who can evaluate, use, and collaborate with AI tools in professional settings (Mogavi et al., 2024; Sergeeva et al., 2025). This demand is particularly relevant for business education, where AI is used in analytics, customer relationship management, operations, finance, marketing, and decision support (Cetindamar et al., 2024).

In Indonesia, the urgency of AI integration in higher education has received growing policy and institutional attention. However, empirical evidence on how Indonesian business students understand, perceive, and intend to use AI tools remains limited (Dabis & Csaki, 2024). This limitation matters because AI adoption in higher education is not only a technical issue, but also a pedagogical, behavioral, and institutional issue. Students may be exposed to AI tools, yet the translation of AI knowledge into meaningful academic use depends on their perceived usefulness, perceived ease of use, confidence, and institutional environment.

This study uses the concept of AI fluency to capture this translation process. In this article, AI literacy refers to students' knowledge and awareness of AI concepts, capabilities, limitations, and applications. AI readiness refers to preparedness to engage with AI. AI competence refers to demonstrated ability or task performance. AI acceptance refers to favorable attitudes and willingness to adopt AI. AI fluency, by contrast, refers to the perceived readiness and intention to apply AI tools confidently, consistently, and appropriately in academic-business contexts. This distinction is important because students may understand AI conceptually without being willing or confident to use it in practice, and they may intend to use AI without yet demonstrating objective competence.

The theoretical gap addressed in this study is therefore not merely the limited Indonesian evidence or the limited focus on business students. Rather, the unresolved issue is how domain-specific AI knowledge becomes translated into technology-acceptance beliefs and intention-based fluency. Prior studies often examine AI literacy and technology acceptance separately, which makes it difficult to explain whether AI knowledge acts as a direct driver of adoption intention, an indirect antecedent through TAM beliefs, or a condition whose effect depends on digital self-efficacy. This gap is particularly salient for generative AI, where ease of access may create high intention even when users' actual skills remain uneven.

To address this issue, the study develops and tests an extended TAM framework integrating AI literacy, perceived usefulness, perceived ease of use, attitude toward using AI, digital self-efficacy, institutional support, and behavioral intention to use AI tools. TAM is retained because the study focuses on individual technology acceptance and the belief-intention mechanism. Digital self-efficacy is added to explain why similar levels of AI literacy may produce different levels of behavioral intention, while institutional support is included to capture the enabling role of the university environment.

The contribution of this research is threefold. First, it clarifies the conceptual boundary between AI literacy and AI fluency by positioning behavioral intention as a proxy for perceived and intention-based fluency, not as a complete measure of objective AI capability. Second, it extends TAM by showing how AI literacy functions as an antecedent

to perceived usefulness, perceived ease of use, and behavioral intention in an Indonesian business education setting. Third, it explains the moderating role of digital self-efficacy and the contextual role of institutional support, thereby providing a more nuanced account of AI adoption than a simple confirmation of standard TAM relationships.

The remainder of this paper is organized as follows. The next section critically reviews AI literacy and fluency frameworks, technology acceptance theories, digital self-efficacy, and institutional support. The method section describes the research design, measurement, sampling, and analytical procedures. The results and discussion sections present the PLS-SEM findings, theoretical interpretation, and alternative explanations. The paper concludes with implications, limitations, and directions for future research.

## **REVIEW OF LITERATURE**

### **AI Literacy and Fluency Frameworks in Higher Education**

AI literacy has generally been defined as a set of competencies that enables individuals to understand, evaluate, communicate with, and use AI systems in daily, educational, and workplace contexts (Long & Magerko, 2020; Ng et al., 2021, 2023). This literature is valuable because it identifies the knowledge base required for responsible AI use. However, literacy alone does not automatically indicate adoption or performance. A student may know what AI can do, but may still avoid using it, use it superficially, or lack confidence when applying it to business tasks.

Recent AI competency frameworks distinguish knowledge, skills, ethical judgment, integration capability, and affective readiness (Chee et al., 2025; Schleiss et al., 2025). These frameworks suggest that AI fluency is broader than awareness but should not be equated with objective expertise unless actual performance is assessed. For this reason, the present study treats AI fluency as an intention-based and perception-based construct: it captures students' self-reported readiness and intention to apply AI tools in academic-business contexts. This operationalization is useful for explaining early-stage adoption, while still requiring caution because behavioral intention is not equivalent to demonstrated AI competence.

Conceptually, AI literacy, AI readiness, AI competence, AI acceptance, and AI fluency occupy different positions. AI literacy concerns understanding and awareness. AI readiness concerns preparedness to engage with AI tools. AI competence concerns demonstrated task performance or proficiency. AI acceptance concerns favorable beliefs, attitudes, and intention toward adoption. AI fluency connects these domains by focusing on the perceived ability and willingness to use AI consistently and appropriately in situated tasks. This boundary reduces conceptual overlap and clarifies why this study combines AI literacy with TAM rather than treating AI literacy as the final outcome.

In business education, this distinction is particularly important. Business students require not only awareness of AI concepts but also confidence in applying AI to marketing analytics, financial forecasting, operations, entrepreneurship, and decision-making cases. Previous studies on business educators and employees highlight the importance of structured training, ethical understanding, data literacy, and domain-specific application (Cetindamar et al., 2024; Saeger et al., 2024). Yet these studies also show that institutional exposure and curriculum design vary widely, making it necessary to examine how student-level literacy becomes translated into acceptance-oriented fluency.

## **Technology Acceptance Model and AI Adoption in Education**

The Technology Acceptance Model (TAM), developed by Davis (1989), explains technology adoption through perceived usefulness and perceived ease of use. Its strength lies in explaining how individual beliefs shape attitude and behavioral intention. For AI tools in education, TAM remains relevant because students frequently evaluate AI based on whether it improves academic performance and whether it is easy to learn and integrate into coursework.

Nevertheless, relying solely on TAM can create theoretical predictability: perceived usefulness and perceived ease of use have been validated repeatedly across educational technology contexts (Granic & Marangunic, 2019; Sanchez-Prieto et al., 2016). In the context of AI, a stronger contribution requires explaining what antecedents, boundary conditions, or contextual factors alter these familiar relationships. This study therefore uses TAM as the baseline belief-intention mechanism rather than as the entire theoretical contribution.

Alternative frameworks provide complementary but different emphases. UTAUT explains acceptance through performance expectancy, effort expectancy, social influence, and facilitating conditions, but its broad adoption predictors are less focused on the conceptual role of AI literacy as domain-specific knowledge. TPACK is useful for teacher pedagogy and instructional design, but it is less suited to modeling students' acceptance intentions. Innovation Diffusion Theory explains the spread of innovation through attributes such as relative advantage and compatibility, but does not directly specify the literacy-belief-intention pathway. Social Cognitive Theory explains self-efficacy and confidence, but does not by itself model technology usefulness and ease-of-use beliefs.

For these reasons, this study positions TAM as the main framework, while using AI literacy as a domain-specific antecedent, digital self-efficacy as a social-cognitive moderator, and institutional support as a contextual enabler. This integration responds to the need for a model that is parsimonious enough to test student AI adoption, but sufficiently extended to explain why AI knowledge may not translate uniformly into intention-based fluency.

### **Critical Positioning of TAM Against Alternative Frameworks**

The comparison above does not imply that TAM is superior in all AI education contexts. Rather, TAM is most appropriate for the present research question because the study seeks to explain how AI literacy shapes usefulness, ease-of-use, attitude, and behavioral intention among students. UTAUT would be stronger if the main objective were to compare social influence and facilitating conditions across user groups. TPACK would be stronger for faculty-level pedagogical integration. Innovation Diffusion Theory would be stronger for institutional-level diffusion over time. Social Cognitive Theory is incorporated selectively through digital self-efficacy because confidence is expected to condition whether AI literacy becomes behavioral intention.

### **AI Literacy's Role in Technology Acceptance**

Emerging research suggests that AI literacy is associated with AI acceptance, but the mechanism remains undertheorized. Some studies imply that literacy increases perceived usefulness and perceived ease of use because knowledgeable students understand what AI can do and how it can be applied. Other studies suggest a more direct pathway in which literacy itself produces intention because students who understand AI feel more prepared to use it. These alternative explanations require empirical testing within a single model.

The present study therefore treats AI literacy as both a direct predictor of behavioral intention and an indirect antecedent operating through TAM beliefs. This dual role is theoretically important because it prevents AI literacy from being treated merely as background knowledge. Instead, AI literacy becomes a mechanism that shapes how students interpret AI tools: as useful, manageable, and relevant to their academic work.

At the same time, the relationship between literacy and intention may be inflated if all constructs are measured by self-report instruments. Students who evaluate themselves positively on AI literacy may also report higher usefulness and intention due to response consistency. This possibility is addressed through procedural controls, reliability and validity assessment, and cautious interpretation of the model's explanatory power.

### **Digital Self-Efficacy and Institutional Support**

Digital self-efficacy, rooted in Bandura's (1997) social cognitive theory, refers to students' belief that they can perform technology-related tasks successfully. In AI adoption, self-efficacy matters because students may possess AI-related knowledge yet hesitate to apply AI tools if they lack confidence in troubleshooting, evaluating outputs, or integrating AI into assignments. Thus, self-efficacy is expected to strengthen the relationship between AI literacy and behavioral intention.

The moderation mechanism can be explained through perceived control and mastery expectations. When digital self-efficacy is high, AI literacy is more likely to become intention because students believe they can convert knowledge into action. When self-efficacy is low, students may understand AI conceptually but avoid use because they anticipate errors, uncertainty, or lack of control. This mechanism is especially relevant for junior students who are still building academic and technological confidence.

Institutional support is treated as a contextual enabler rather than a single undifferentiated resource. It may include technical support, policy support, faculty encouragement, infrastructure access, and financial or licensing support. These dimensions can shape perceived usefulness and perceived ease of use by making AI tools more accessible, legitimate, and pedagogically integrated. Because the present instrument measures institutional support at a general level, the findings should be interpreted as evidence of perceived overall support rather than as evidence for any specific support dimension.

### **Research Gaps and Study Positioning**

Three gaps motivate this study. The first is contextual: empirical evidence on AI adoption among Indonesian business students remains limited compared with evidence from Western and East Asian contexts. The second is conceptual: AI literacy, AI readiness, AI competence, AI acceptance, and AI fluency are often used in overlapping ways, creating ambiguity about what is actually being measured. The third and most important gap is theoretical: existing research has not sufficiently explained how AI literacy is transformed into acceptance-oriented AI fluency through perceived usefulness, perceived ease of use, attitude, self-efficacy, and institutional support.

This study addresses these gaps by integrating AI literacy into an extended TAM framework and testing it among Indonesian business students. The model examines AI literacy as a domain-specific antecedent, digital self-efficacy as a boundary condition, and institutional support as a contextual enabler. This positioning enables the study to contribute beyond contextual replication by explaining the mechanism through which AI knowledge

becomes intention-based fluency, while also acknowledging that objective AI competence requires additional performance-based measurement.

## RESEARCH METHOD

### Research Framework and Hypotheses

This study employs a quantitative cross-sectional research design grounded in the Technology Acceptance Model (TAM), extended with AI literacy, digital self-efficacy, and institutional support. The conceptual model proposes that AI literacy influences perceived usefulness, perceived ease of use, and behavioral intention; perceived usefulness and perceived ease of use influence attitude; attitude influences behavioral intention; digital self-efficacy moderates the AI literacy-behavioral intention relationship; and institutional support influences perceived usefulness and perceived ease of use. The design is appropriate for testing perceived and intention-based AI fluency, but it does not establish causality or measure actual AI performance.

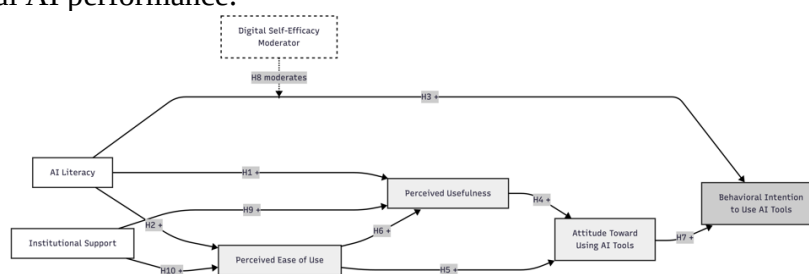


Figure 1.

### Conceptual Framework

The following hypotheses were formulated:

**H1:** AI literacy positively influences perceived usefulness of AI tools. **H2:** AI literacy positively influences perceived ease of use of AI tools. **H3:** AI literacy positively influences behavioral intention to use AI tools. **H4:** Perceived usefulness positively influences attitude toward using AI tools. **H5:** Perceived ease of use positively influences attitude toward using AI tools. **H6:** Perceived ease of use positively influences perceived usefulness. **H7:** Attitude toward using AI tools positively influences behavioral intention. **H8:** Digital self-efficacy moderates the relationship between AI literacy and behavioral intention. **H9:** Institutional support positively influences perceived usefulness. **H10:** Institutional support positively influences perceived ease of use.

### Participants and Sampling

The target population comprised undergraduate business students at Universitas Bunda Mulia enrolled during the 2024/2025 academic year. Using G\*Power 3.1 software, we calculated a minimum sample size of 350 participants to achieve 80% statistical power with a medium effect size ( $f^2 = 0.15$ ) and significance level  $\alpha = 0.05$ , accounting for 10 predictor variables in the structural model.

We employed stratified random sampling to ensure representation across academic years (first through fourth year) and business programs (Management and Digital Business). From a population of approximately 2,400 business students, 450 were invited to participate, yielding 385 complete responses (response rate = 85.6%). Participants ranged in age from 18

to 24 years ( $M = 20.3$ ,  $SD = 1.4$ ), with 58% female and 42% male. Distribution across academic years was relatively balanced: Year 1 (26%), Year 2 (24%), Year 3 (28%), Year 4 (22%).

### Measurement Instrument

We developed a questionnaire comprising seven constructs, drawing on validated scales and adapting them to the AI-in-business-education context. All items used a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument was designed to measure perceived AI literacy, TAM beliefs, self-efficacy, attitude, institutional support, and behavioral intention. Because the study relies on self-report data, the results capture perceived knowledge and intention-based fluency rather than externally assessed AI competence.

**AI Literacy (7 items):** Adapted from Carolus et al. (2023) and Ng et al. (2024), this scale measured students' understanding of AI concepts, awareness of AI capabilities and limitations, and ability to recognize AI applications in business contexts. Sample items included: "I understand the basic principles of how AI systems learn from data" and "I can identify appropriate business situations where AI tools would be useful."

**Perceived Usefulness (5 items):** Based on Davis (1989) and adapted for AI tools in business education. Sample items included: "Using AI tools helps me complete academic assignments more effectively" and "AI tools improve the quality of my academic work."

**Perceived Ease of Use (5 items):** Also based on Davis (1989), measuring the extent to which students believed AI tools were easy to use. Sample items included: "Learning to use AI tools is easy for me" and "I find AI tools intuitive and user-friendly."

**Digital Self-Efficacy (6 items):** Adapted from Bandura (1997) and Jeilani & Abubakar (2025), measuring students' confidence in their ability to use AI technologies. Sample items included: "I am confident I can learn to use new AI tools when needed" and "I can solve problems that arise when using AI applications."

**Attitude Toward Using AI (4 items):** Measuring students' overall evaluation of using AI tools, based on Ibrahim et al. (2025). Sample items included: "Using AI tools in my studies is a good idea" and "I have a positive opinion about AI tools in business education."

**Behavioral Intention to Use AI (4 items):** Measuring students' plans and willingness to use AI tools, adapted from Venkatesh et al. (2003). Sample items included: "I intend to use AI tools regularly in my academic work" and "I plan to use AI tools for business-related assignments and projects." In this study, behavioral intention is used as a proxy for perceived and intention-based AI fluency, not as a direct measure of actual AI usage or objective proficiency.

**Institutional Support (5 items):** Developed based on Jeilani and Abubakar (2025) and Almasri (2024), measuring perceived university support for AI use. Sample items included: "My university provides adequate resources for learning about AI tools" and "Faculty members encourage the appropriate use of AI in coursework." Conceptually, institutional support may include technical, policy, faculty, infrastructure, and financial support; however, the present scale captures students' overall perception of institutional support rather than separate subdimensions.

The questionnaire was initially developed in English and then translated into Indonesian using back-translation procedures to ensure linguistic equivalence. Three bilingual experts

reviewed both versions and resolved discrepancies through consensus. A pilot study with 40 business students confirmed the clarity and relevance of items.

### **Data Collection Procedures**

Data collection occurred over four weeks in October-November 2024. We distributed the questionnaire through multiple channels to maximize response rates: online via Google Forms, in-person during designated class sessions (with instructor permission), and through student organization networks. Participation was voluntary and anonymous. Students received an information sheet explaining the study's purpose, data handling procedures, and their right to withdraw.

The survey began with demographic questions (age, gender, academic year, major, previous AI training) followed by the main questionnaire items presented in randomized order to minimize order effects. Attention check items were embedded to identify careless responding. Respondents who failed more than one attention check ( $n = 8$ ) were excluded from analysis. Procedural remedies to reduce common method bias included anonymity, voluntary participation, neutral wording, randomized item order, and separation of demographic and construct items. Nevertheless, because all main constructs were measured through the same questionnaire at one point in time, common method variance cannot be fully eliminated.

### **Data Analysis Approach**

We employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0. PLS-SEM was selected because the study aimed to explain variance in behavioral intention and examine an extended model in a developing research context. The approach is suitable for prediction-oriented analysis, but the results are interpreted cautiously as cross-sectional associations rather than causal effects.

The analysis proceeded in two stages following established PLS-SEM procedures (Hair et al., 2019; Sarstedt et al., 2021).

**Stage 1: Measurement Model Assessment.** We evaluated internal consistency reliability using Composite Reliability (CR) and Cronbach's alpha, convergent validity using Average Variance Extracted (AVE) and factor loadings, and discriminant validity using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio.

**Stage 2: Structural Model Assessment.** After confirming measurement model quality, we assessed path coefficients and significance levels through bootstrapping with 5,000 resamples, coefficient of determination ( $R^2$ ), effect sizes ( $f^2$ ), predictive relevance ( $Q^2$ ), and model fit indicators including SRMR and NFI. Because high explained variance can partly reflect conceptual proximity among self-reported perceptual constructs,  $R^2$  values were interpreted alongside effect sizes, theoretical plausibility, and study limitations.

Moderation analysis for H8 was conducted using the two-stage approach in SmartPLS, where latent variable scores from the main model were used to create interaction terms included in a separate structural model. The interaction was interpreted through social cognitive theory, emphasizing the role of self-efficacy in converting knowledge into action-oriented intention.

Prior to PLS-SEM analysis, we conducted preliminary analyses to examine data distribution, identify outliers, and assess multicollinearity through variance inflation factors (VIF). All VIF values were below 3.0, indicating no multicollinearity concerns in the structural model. Harman's single-factor test was also inspected as an initial common method bias diagnostic.

However, because no marker variable was included in the original instrument, common method bias remains a limitation and should be addressed more rigorously in future studies using marker variables, temporal separation, objective performance indicators, or multi-source data. Descriptive statistics and group comparisons were conducted using SPSS 27.0.

## RESULTS AND DISCUSSION

### Descriptive Statistics and Preliminary Analyses

Descriptive statistics for all latent constructs are presented in Table 1. Overall, business students at Universitas Bunda Mulia demonstrated moderate levels of AI literacy ( $M = 3.24$ ,  $SD = 0.82$ ), perceived usefulness ( $M = 3.68$ ,  $SD = 0.76$ ), perceived ease of use ( $M = 3.41$ ,  $SD = 0.84$ ), digital self-efficacy ( $M = 3.52$ ,  $SD = 0.79$ ), attitude toward using AI ( $M = 3.71$ ,  $SD = 0.81$ ), and behavioral intention to use AI ( $M = 3.59$ ,  $SD = 0.88$ ). Institutional support received the lowest mean score ( $M = 2.89$ ,  $SD = 0.93$ ), suggesting that students perceived limited university-level support for AI integration.

**Table 1.** Descriptive Statistics and Correlations for Latent Constructs

| Construct                | M    | SD   | 1    | 2    | 3    | 4    | 5    | 6    | 7    |
|--------------------------|------|------|------|------|------|------|------|------|------|
| AI Literacy              | 3.24 | 0.82 | 1.00 |      |      |      |      |      |      |
| Perceived Usefulness     | 3.68 | 0.76 | 0.52 | 1.00 |      |      |      |      |      |
| Perceived Ease of Use    | 3.41 | 0.84 | 0.48 | 0.56 | 1.00 |      |      |      |      |
| Digital Self-Efficacy    | 3.52 | 0.79 | 0.45 | 0.47 | 0.44 | 1.00 |      |      |      |
| Attitude Toward Using AI | 3.71 | 0.81 | 0.51 | 0.62 | 0.53 | 0.48 | 1.00 |      |      |
| Behavioral Intention     | 3.59 | 0.88 | 0.54 | 0.58 | 0.49 | 0.52 | 0.68 | 1.00 |      |
| Institutional Support    | 2.89 | 0.93 | 0.34 | 0.38 | 0.41 | 0.36 | 0.42 | 0.39 | 1.00 |

Skewness values ranged from -0.42 to 0.38, and kurtosis values ranged from -0.67 to 0.52, indicating acceptable normality of distributions (Kline, 2016). Correlation analyses revealed significant positive relationships among all constructs ( $r = 0.34$  to  $0.68$ , all  $p < 0.001$ ), with the strongest correlation observed between attitude toward using AI and behavioral intention ( $r = 0.68$ ).

Group comparisons revealed significant differences in AI literacy by academic year,  $F(3, 381) = 8.34$ ,  $p < 0.001$ ,  $\eta^2 = 0.062$ . Post-hoc Tukey tests indicated that fourth-year students ( $M = 3.52$ ,  $SD = 0.78$ ) scored significantly higher than first-year students ( $M = 2.98$ ,  $SD = 0.83$ ,  $p < 0.001$ ) and second-year students ( $M = 3.14$ ,  $SD = 0.79$ ,  $p = 0.012$ ). No significant differences were found between third-year and fourth-year students. These patterns suggest that AI literacy develops progressively throughout undergraduate education, likely reflecting accumulated exposure to AI concepts and applications.

Gender comparisons revealed no significant differences in AI literacy,  $t(383) = 1.42$ ,  $p = 0.156$ , but male students reported significantly higher digital self-efficacy ( $M = 3.68$ ,  $SD = 0.75$ ) compared to female students ( $M = 3.41$ ,  $SD = 0.81$ ),  $t(383) = 2.87$ ,  $p = 0.004$ ,  $d =$

0.35. This finding aligns with previous research on gender differences in technology self-efficacy, suggesting that confidence gaps persist despite equivalent knowledge levels.

Students who reported previous AI training or coursework ( $n = 156$ , 40.5%) demonstrated significantly higher AI literacy ( $M = 3.58$ ,  $SD = 0.74$ ) compared to those without prior training ( $M = 3.01$ ,  $SD = 0.82$ ),  $t(383) = 6.83$ ,  $p < 0.001$ ,  $d = 0.73$ . They also reported higher perceived ease of use ( $M = 3.68$ ,  $SD = 0.78$  vs.  $M = 3.23$ ,  $SD = 0.85$ ,  $t(383) = 5.21$ ,  $p < 0.001$ ,  $d = 0.56$ ) and behavioral intention ( $M = 3.88$ ,  $SD = 0.79$  vs.  $M = 3.40$ ,  $SD = 0.91$ ,  $t(383) = 5.34$ ,  $p < 0.001$ ,  $d = 0.57$ ). These findings underscore the importance of structured AI education in building both competence and confidence.

### Measurement Model Assessment

All constructs demonstrated satisfactory reliability and validity. Composite reliability values ranged from 0.87 to 0.94, and Cronbach's alpha values ranged from 0.84 to 0.92, well above the recommended threshold of 0.70 (Hair et al., 2019). Factor loadings for all items exceeded 0.70, ranging from 0.73 to 0.91, indicating strong relationships between indicators and their respective constructs. Average variance extracted (AVE) values ranged from 0.62 to 0.76, surpassing the minimum criterion of 0.50 and confirming adequate convergent validity.

**Table 2.** Measurement Model Assessment: Reliability and Validity

| Construct                | Items | Cronbach $\alpha$ | CR   | AVE  | Factor Loadings Range |
|--------------------------|-------|-------------------|------|------|-----------------------|
| AI Literacy              | 7     | 0.89              | 0.91 | 0.63 | 0.75-0.84             |
| Perceived Usefulness     | 5     | 0.87              | 0.90 | 0.65 | 0.78-0.87             |
| Perceived Ease of Use    | 5     | 0.88              | 0.89 | 0.62 | 0.73-0.82             |
| Digital Self-Efficacy    | 6     | 0.91              | 0.93 | 0.69 | 0.79-0.91             |
| Attitude Toward Using AI | 4     | 0.84              | 0.87 | 0.63 | 0.76-0.83             |
| Behavioral Intention     | 4     | 0.86              | 0.88 | 0.64 | 0.77-0.86             |
| Institutional Support    | 5     | 0.92              | 0.94 | 0.76 | 0.84-0.90             |

Discriminant validity was confirmed through multiple criteria. The Fornell-Larcker criterion showed that the square root of AVE for each construct exceeded all its correlations with other constructs. The more stringent Heterotrait-Monotrait (HTMT) ratio test revealed values ranging from 0.42 to 0.79, all below the conservative threshold of 0.85, confirming that constructs were empirically distinct. Cross-loadings analysis further confirmed discriminant validity, with each indicator loading highest on its intended construct.

### Structural Model Assessment

The structural model demonstrated acceptable fit with  $SRMR = 0.068$  ( $< 0.08$  threshold) and  $NFI = 0.884$  (approaching 0.90 threshold). The model explained substantial variance in key endogenous variables: behavioral intention to use AI ( $R^2 = 0.523$ ), attitude

toward using AI ( $R^2 = 0.487$ ), perceived usefulness ( $R^2 = 0.412$ ), and perceived ease of use ( $R^2 = 0.368$ ). These  $R^2$  values indicate moderate to substantial explanatory power. However, because the constructs were measured using the same self-reported instrument and are theoretically related, the explained variance should be interpreted as evidence of a coherent perceptual adoption model rather than definitive proof of objective AI fluency.

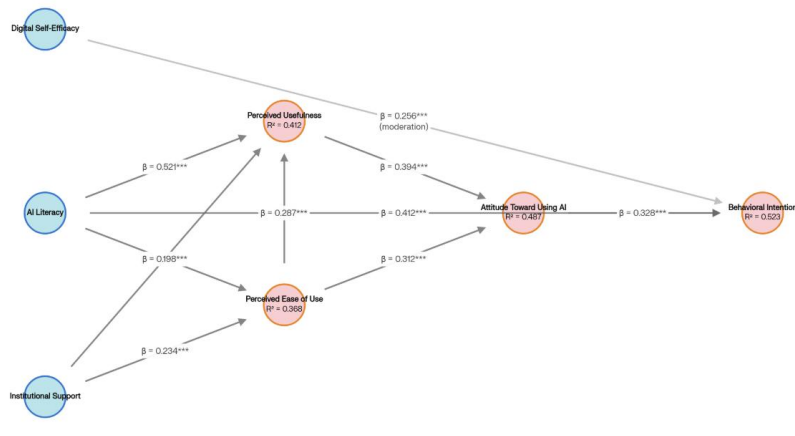


**Figure 2.** Structural Model with Path Coefficients

Path analysis results, presented in Table 3, supported the proposed relationships. AI literacy significantly predicted behavioral intention directly ( $\beta = 0.412$ ,  $t = 8.74$ ,  $p < 0.001$ ,  $f^2 = 0.245$ ), perceived usefulness ( $\beta = 0.521$ ,  $t = 11.23$ ,  $p < 0.001$ ,  $f^2 = 0.372$ ), and perceived ease of use ( $\beta = 0.486$ ,  $t = 9.87$ ,  $p < 0.001$ ,  $f^2 = 0.309$ ), supporting H1, H2, and H3. These effects suggest that AI literacy functions not only as background knowledge but also as a domain-specific antecedent that shapes students' usefulness beliefs, ease-of-use beliefs, and intention-based AI fluency.

**Table 3.** Structural Model Path Coefficients and Hypothesis Testing

| Hypothesis                                                                   | $\beta$ | t-value | p-value | $f^2$ | Decision  |
|------------------------------------------------------------------------------|---------|---------|---------|-------|-----------|
| H1: AI Literacy $\rightarrow$ Perceived Usefulness                           | 0.521   | 11.23   | <0.001  | 0.372 | Supported |
| H2: AI Literacy $\rightarrow$ Perceived Ease of Use                          | 0.486   | 9.87    | <0.001  | 0.309 | Supported |
| H3: AI Literacy $\rightarrow$ Behavioral Intention                           | 0.412   | 8.74    | <0.001  | 0.245 | Supported |
| H4: Perceived Usefulness $\rightarrow$ Attitude                              | 0.394   | 7.21    | <0.001  | 0.198 | Supported |
| H5: Perceived Ease of Use $\rightarrow$ Attitude                             | 0.312   | 6.03    | <0.001  | 0.124 | Supported |
| H6: Perceived Ease of Use $\rightarrow$ Perceived Usefulness                 | 0.287   | 5.44    | <0.001  | 0.106 | Supported |
| H7: Attitude $\rightarrow$ Behavioral Intention                              | 0.328   | 6.89    | <0.001  | 0.156 | Supported |
| H8: Digital Self-Efficacy $\times$ AI Literacy $\rightarrow$ BI (Moderation) | 0.256   | 4.32    | <0.001  | 0.089 | Supported |

|                                                    |       |      |        |       |           |
|----------------------------------------------------|-------|------|--------|-------|-----------|
| H9: Institutional Support → Perceived Usefulness   | 0.198 | 3.87 | <0.001 | 0.052 | Supported |
| H10: Institutional Support → Perceived Ease of Use | 0.234 | 4.62 | <0.001 | 0.071 | Supported |

Perceived usefulness significantly influenced attitude toward using AI ( $\beta = 0.394$ ,  $t = 7.21$ ,  $p < 0.001$ ,  $f^2 = 0.198$ ), supporting H4. Similarly, perceived ease of use positively affected attitude ( $\beta = 0.312$ ,  $t = 6.03$ ,  $p < 0.001$ ,  $f^2 = 0.124$ ) and perceived usefulness ( $\beta = 0.287$ ,  $t = 5.44$ ,  $p < 0.001$ ,  $f^2 = 0.106$ ), supporting H5 and H6. These findings align with classic TAM relationships, confirming that students who viewed AI tools as useful and easy to use developed more positive attitudes toward their adoption.

Attitude toward using AI strongly predicted behavioral intention ( $\beta = 0.328$ ,  $t = 6.89$ ,  $p < 0.001$ ,  $f^2 = 0.156$ ), supporting H7. This relationship demonstrated that affective evaluations translated into concrete plans for AI tool usage, consistent with the theory of planned behavior and TAM extensions.

Institutional support significantly influenced both perceived usefulness ( $\beta = 0.198$ ,  $t = 3.87$ ,  $p < 0.001$ ,  $f^2 = 0.052$ ) and perceived ease of use ( $\beta = 0.234$ ,  $t = 4.62$ ,  $p < 0.001$ ,  $f^2 = 0.071$ ), supporting H9 and H10. Although the effect sizes were small, the findings indicate that students' perceptions of university-level support are associated with how useful and manageable they perceive AI tools to be. Because institutional support was measured broadly, the results do not identify which form of support - technical, policy, faculty, infrastructure, or financial - is most influential. Future studies should disaggregate these dimensions.

### **Moderation Analysis**

The moderation analysis revealed that digital self-efficacy significantly moderated the relationship between AI literacy and behavioral intention ( $\beta = 0.256$ ,  $t = 4.32$ ,  $p < 0.001$ ,  $f^2 = 0.089$ ), supporting H8. This result indicates that AI literacy has a stronger association with intention-based AI fluency when students believe they can handle digital tools effectively. From a social cognitive perspective, self-efficacy operates as a psychological bridge between knowing and doing: knowledge is more likely to become intention when students feel capable of applying that knowledge, managing uncertainty, and solving problems during AI use.

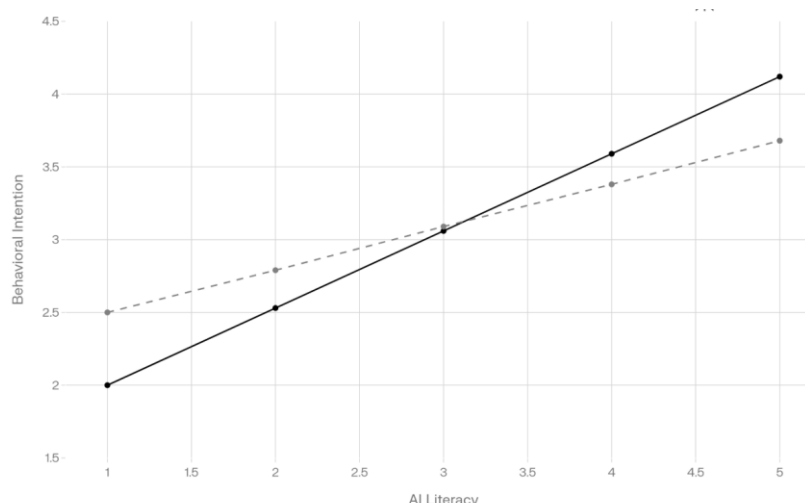


**Figure 3.** Moderation Effect of Digital Self-Efficacy on AI Literacy → Behavioral Intention Relationship

The moderation effect was particularly pronounced among first- and second-year students ( $\beta = 0.341$ ,  $t = 4.78$ ,  $p < 0.001$ ), but it was not significant among third- and fourth-year students ( $\beta = 0.098$ ,  $t = 1.23$ ,  $p = 0.218$ ). This pattern suggests that self-efficacy matters most during the early stages of academic and technological adjustment. More senior students may have accumulated enough exposure to AI-related tasks that their literacy translates into intention with less dependence on confidence. An alternative explanation is that senior students have more stable academic routines, making their AI intention less sensitive to self-efficacy differences.

#### Predictive Relevance and Effect Sizes

Blindfolding procedures confirmed the model's predictive relevance, with  $Q^2$  values exceeding zero for all endogenous constructs: behavioral intention ( $Q^2 = 0.376$ ), attitude ( $Q^2 = 0.334$ ), perceived usefulness ( $Q^2 = 0.281$ ), and perceived ease of use ( $Q^2 = 0.252$ ). These positive  $Q^2$  values indicated that the model had substantial predictive power beyond the sample, supporting its generalizability.

Effect size analysis revealed that AI literacy had the largest total effect on behavioral intention (total effect = 0.647), followed by attitude (total effect = 0.328) and digital self-efficacy (total effect = 0.256). This finding underscored AI literacy as the most influential predictor of students' intentions to use AI tools in their academic work, operating through both direct and indirect pathways mediated by perceived usefulness, perceived ease of use, and attitude.

#### Importance-Performance Map Analysis

To identify priorities for institutional interventions, we conducted importance-performance map analysis (IPMA) with behavioral intention as the target construct. Results indicated that AI literacy demonstrated both high importance (total effect = 0.647) and moderate performance (unstandardized latent variable scores,  $M = 3.24$ ), positioning it as a high-priority area for improvement. Institutional support showed moderate importance (total effect = 0.143 through indirect pathways) but low performance ( $M = 2.89$ ), identifying it as another critical intervention point.

In contrast, attitude toward using AI exhibited high performance ( $M = 3.71$ ) but moderate importance (total effect = 0.328), suggesting that while students generally held positive attitudes, these alone were insufficient without corresponding literacy and self-efficacy. Digital self-efficacy demonstrated moderate levels of both importance and performance, indicating adequate but improvable standing.

#### **Discussion: Theoretical Interpretation and Alternative Explanations**

The findings should be interpreted as more than a confirmation of familiar TAM relationships. The strongest effects came from AI literacy, suggesting that in AI-enabled learning environments, domain-specific knowledge may precede and shape the classic TAM beliefs of usefulness and ease of use. This supports the argument that AI adoption differs from ordinary educational technology adoption because students must not only perceive a tool as useful, but also understand its capabilities, limitations, and appropriate applications.

At the same time, the model's high level of support may partly reflect the conceptual closeness of perceptual variables measured through a single survey. Therefore, the supported hypotheses should not be read as evidence that the model fully captures AI fluency. Rather, they show that students' perceived AI literacy, usefulness beliefs, ease-of-use beliefs, attitudes, and intentions form a coherent adoption pattern. Actual fluency would require additional evidence from AI task performance, usage logs, project outputs, or longitudinal tracking.

The Indonesian context also deserves attention. The low mean score for institutional support ( $M = 2.89$ ) suggests that students may already hold positive attitudes toward AI while still perceiving the institutional environment as underdeveloped. This tension may reflect the rapid diffusion of publicly available AI tools outside formal university systems. As a result, students may learn AI informally before universities develop clear policies, structured training, or curriculum integration.

The nonsignificant difference in AI literacy by gender, combined with significant differences in digital self-efficacy, provides another theoretical insight. Knowledge gaps and confidence gaps are not identical. Students may report comparable knowledge but differ in their confidence to use AI tools. This reinforces the value of integrating social cognitive theory into TAM-based AI adoption research and suggests that interventions should address confidence-building, not only knowledge transmission.

## **CONCLUSION**

### **Theoretical Implications**

This study makes several theoretical contributions to research on AI fluency and technology acceptance in higher education. First, it clarifies that AI literacy and AI fluency are related but distinct. AI literacy reflects knowledge and awareness, while the present operationalization of AI fluency reflects perceived readiness and intention to apply AI tools in academic-business contexts. This distinction is important because it avoids overstating behavioral intention as objective capability.

Second, the study extends TAM by positioning AI literacy as a domain-specific antecedent to perceived usefulness, perceived ease of use, and behavioral intention. This contribution moves beyond simply adding another external variable to TAM; it explains how knowledge about AI shapes the belief-intention mechanism that underlies technology adoption.

Third, the moderation effect of digital self-efficacy identifies a boundary condition for the AI literacy-behavioral intention relationship. Students with higher digital self-efficacy appear more able to convert AI-related knowledge into intention to use AI tools. This finding links TAM with social cognitive theory and highlights the psychological mechanism through which confidence supports adoption-oriented AI fluency.

Fourth, the results contribute to understanding AI adoption in an Indonesian higher education context. The relatively low perception of institutional support, combined with significant effects on TAM beliefs, suggests that institutional environments still matter even when students have access to AI tools independently. However, this conclusion should be treated as context-specific because the sample came from a single private university in Jakarta.

### **Practical Implications for Business Education**

The findings suggest several cautious practical implications for business education. Because AI literacy showed the strongest total effect on behavioral intention, business programs may consider integrating AI literacy more systematically across the curriculum. However, these recommendations should be treated as evidence-informed suggestions rather than definitive prescriptions, because the study measured perceptions and intentions rather than learning outcomes or actual AI performance.

A scaffolded approach may be appropriate. Early courses may introduce AI concepts, ethical issues, data literacy, and limitations of AI-generated output. Intermediate courses may embed AI applications in marketing, finance, operations, entrepreneurship, and management assignments. Advanced courses may use project-based tasks where students evaluate AI tools for business problem-solving. Such integration should be assessed through objective tasks or portfolio evidence in future studies.

The significant moderation effect of digital self-efficacy suggests that AI education should include confidence-building activities, especially for junior students. Low-stakes workshops, guided practice, peer mentoring, and troubleshooting exercises may help students convert knowledge into actual use. These interventions are consistent with the finding that self-efficacy strengthens the relationship between AI literacy and behavioral intention.

The low institutional support score suggests that universities may need clearer AI policies, accessible AI learning resources, faculty guidance, technical support, and infrastructure. Because the present scale did not separate these dimensions, future institutional evaluations should identify which types of support most strongly influence perceived usefulness and ease of use.

The gender difference in digital self-efficacy, despite nonsignificant differences in AI literacy, suggests that interventions should not assume that knowledge and confidence develop equally. Inclusive AI workshops, diverse examples, and supportive learning spaces may help reduce confidence gaps. This implication should be tested further before being generalized across institutions.

### **Implications for Curriculum Development**

Based on the findings, a possible AI fluency development framework for business education may include four components. This framework is proposed as a practical direction for curriculum discussion, not as a directly tested intervention model.

Component 1: Foundational AI Literacy. Students may be introduced to AI concepts, business applications, ethical concerns, data literacy, and critical evaluation of AI outputs.

Assessment should combine self-report with objective tasks to avoid relying only on perceived literacy.

Component 2: Domain-Specific AI Applications. AI content may be embedded within functional business courses, such as marketing analytics, financial forecasting, human resource analytics, operations optimization, and business strategy. This would help students connect general AI literacy with business-specific use cases.

Component 3: Practical AI Implementation. Project-based learning, case competitions, or capstone assignments may require students to select AI tools, justify their use, evaluate outputs, and reflect on limitations. Such activities would provide stronger evidence of AI competence than behavioral intention alone.

Component 4: Professional Development and Ethics. Workshops and seminars may address emerging AI trends, responsible use, academic integrity, bias, privacy, and career implications. Because AI technologies change quickly, ongoing learning opportunities are needed beyond a single course.

### **Limitations and Directions for Future Research**

Several limitations should be acknowledged. First, this study used a cross-sectional design, so causal relationships cannot be firmly established. Although the hypotheses are grounded in theory, the data show associations among perceptions and intentions at one point in time. Longitudinal designs are needed to examine whether AI literacy leads to changes in perceived usefulness, self-efficacy, actual use, and AI fluency over time.

Second, the study relies on self-reported measures, creating possible common method variance, social desirability bias, and response consistency bias. Procedural controls and preliminary diagnostics reduce but do not eliminate this risk. Future studies should include marker variables, temporal separation, multi-source data, usage logs, or performance-based AI tasks.

Third, the sample came from business students at a single private university in Jakarta. Institutional culture, technology access, curriculum exposure, and student background may differ across public universities, regional institutions, and other disciplines. Multi-institutional and cross-regional samples are needed before generalizing the findings to Indonesian higher education broadly.

Fourth, behavioral intention was used as a proxy for perceived and intention-based AI fluency, not as a direct measure of actual AI use. Students may intend to use AI tools without possessing advanced operational, evaluative, or ethical competence. Future studies should measure actual usage behavior, AI task completion quality, prompt design ability, and critical evaluation of AI-generated output.

Fifth, the study measured general intention to use AI tools rather than adoption of specific AI applications. Acceptance may differ across generative AI assistants, analytics platforms, writing tools, coding tools, and business simulation systems. Future research should examine technology-specific adoption patterns.

Sixth, cultural factors specific to Indonesian higher education were discussed but not directly measured. Variables such as collectivism, power distance, uncertainty avoidance, academic integrity norms, and lecturer authority may shape AI acceptance. Comparative studies across countries and institutional types would strengthen culturally informed theory development.

Seventh, the institutional support construct was measured broadly. Future studies should distinguish technical support, policy support, faculty support, infrastructure support, and financial support. This would allow more precise practical recommendations and stronger theoretical understanding of institutional enablers.

Finally, because AI technologies evolve rapidly, students' perceptions may change as tools become more powerful, accessible, and regulated. Repeated cross-sectional or panel studies are needed to track how AI literacy, self-efficacy, institutional support, and actual fluency develop over time.

### **Concluding Remarks**

This study provides empirical evidence that perceived and intention-based AI fluency among business students is shaped by an interconnected system of AI literacy, usefulness beliefs, ease-of-use beliefs, attitudes, self-efficacy, and institutional support. AI literacy emerged as the most influential antecedent, suggesting that knowledge about AI is central to students' willingness to use AI tools in academic-business contexts.

At the same time, the study cautions against equating intention with actual fluency. The findings support an adoption-oriented understanding of AI fluency, but objective AI competence requires additional evidence from performance-based assessments and actual usage data. This distinction is essential for developing stronger AI education research and more responsible curriculum interventions.

For business education, the implication is that AI integration should combine conceptual literacy, guided practice, confidence-building, ethical reflection, and institutional support. Such an approach can help students move from knowing about AI toward using AI critically and appropriately, while future research should continue to test whether these intentions translate into demonstrable AI capability and responsible professional practice.

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